Assistive Arm and Hand Manipulation: How does current research intersect with actual healthcare needs?

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***Abstract*— Human assistive robotics can help the elderly and those with disabilities with Activities of Daily Living (ADL). Robotics researchers approach this bottom-up publishing on methods for control of different types of movements. Health research on the other hand focuses on hospital clinical assessment and rehabilitation using the International Classification of Functioning (ICF), leaving arguably important differences between each domain. In particular, little is known quantitatively on what ADLs humans perform in their ordinary environment - at home, work etc. This information can guide robotics development and prioritize what technology to deploy for in-home assistive robotics. This study targets several large lifelogging databases, where we compute (i) ADL task frequency from long-term low sampling frequency video and Internet of Things (IoT) sensor data, and (ii) short term arm and hand movement data from 30 fps video data of domestic tasks. Robotics and health care have different terms and taxonomies for representing tasks and motions. From the quantitative ADL task and ICF motion data we derive and discuss a robotics-relevant taxonomy in attempts to ameliorate these taxonomic differences.**

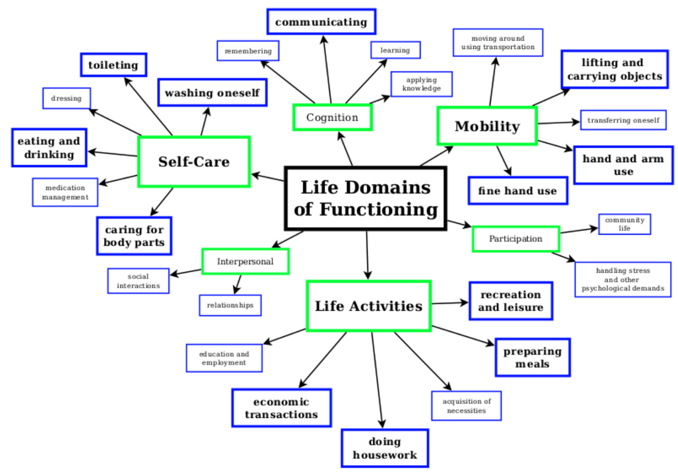

Fig. 1. WHODAS2.0: Life Domains of Functioning

I. Introduction

Human assistive robotics can help the elderly and those with disabilities with Activities of Daily Living (ADL)[1]. Assistive robot arms such as the wheelchair-mountable Kinova Jaco [2] and Manus/iArm [3] have been commercially available for over a decade. Such robot arms can provide increased independence for anyone with disabilities, reduce load on caregivers (both relatives and nurses), and reduce health care costs [4]. Robot arms are potentially as important to upper body disabilities as power wheelchairs have become to lower body disabilities. However, outside of research projects, only a few hundred assistive arms are deployed with disability users, primarily in Europe and North America. To make robotics readers familiar with the health care classification of ADL, we briefly review the World Health Organization Disability Assessment Schedule (WHODAS2.0)[5], and classifications of tasks and motions in the International Classification of Functioning (ICF) [6]. These are primarily developed to determine the level of disability and design corresponding rehabilitation, not to guide assistive robotics research. In health care literature, to the best of our knowledge, there does not appear to be quantitative studies on disabled, or able, human use of ADL tasks and ICF motions; this may be a result of this not being central to rehabilitation, but it is unclear at this time precisely why this is the case. For assistive robotics, knowing what ADL tasks are most important to support, and the needed performance parameters for these tasks will be crucial to increase usability and deployment. This paper hopes to mitigate this quantitative gap. Robots for helping anyone with arm or hand functionality disabilities has been studied since the 1960s. We distinguish here between a physically independent robot arm, typically mounted on the users wheelchair, and prosthesis, where a variable degree of the human functionality is replaced, with the former being our group of interest. Even with the vast research into assistive robotics, of the few assistive robots being utilized, they all still use basic joystick teleoperation[2], [3]. Even with this basic human robot interaction (HRI), United States Veterans Affairs estimate that approximately 150,000 Americans could benefit from a wheelchair mounted arm[7]. With better functionality and ease of use, deployment to larger populations with reduced arm function would be possible.

In the field of Computer Science, recent interest in video object and activity recognition[8][9], and life-logging capture has resulted in numerous public data-sets[10]. We studied over 30 such data-sets to extract tasks of high importance and relevant motion data [11].

Health care and robotic domains have different taxonomies to classify and quantify everyday human tasks and motions,[12], [13], [14], [15], [16], [17]. By combining the taxonomies from both domains, and quantifying health care needs with robotic opportunities we seek to bridge the two,

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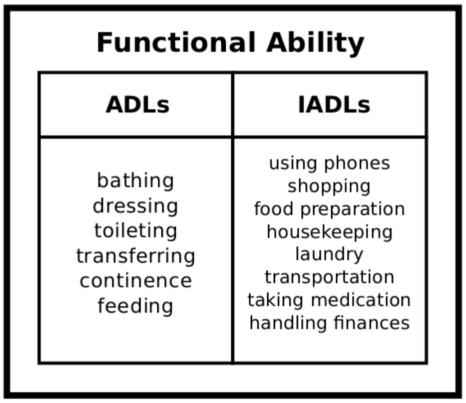

Fig. 2. Measures of Functional Ability: ADLs and IADLs

often separate, communities. This would provide the robotics community baseline information of what human tasks would be of high value to implement on assistive robots.

II. Activities of Daily Living, Self-Care, and Independence

The International Classification of Functioning, Disability and Health (ICF) provides a framework and classification system for determining the overall health of individuals and populations[6]. Disability information is an important indicator of a populations health status, as it shows the impact that functional limitations have on independence. This concept is known as functional disability, or the limitations one may experience in performing independent living tasks [18]. A quantification of functional disability includes both measures of Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs) as shown in Figure 2. The World Health Organization (WHO) further developed WHODAS2.0 from ICF as a standardized, cross-cultural measure of functioning and disability across all life domains[19], see Fig. 1.

A common approach in healthcare research is to ask disabled users and their caregivers (nurses or family members) for their preferences when it comes to robotic assistance [20], [21]. Notably preferences vary a lot, and users opinions shift significantly over time. Particularly caregivers tend to favor tasks such as taking medication, while users favor picking dropped objects and leisure related tasks in pre-automation surveys. 67 users were surveyed after they received and used an assistive robotic arm. Post-automation user preferences had shifted from leisure to work related tasks[7].

III. A Review of Robotics for Assisted Living

A lightweight robotic arm can be attached to a wheelchair and assist the user in ADLs [7]. With such a robot, users with low arm functionality would gain freedom to complete more of their daily tasks independently. While there are many industrial robot arms, only two manufacturers have over 100 systems deployed Dutch Exact Dynamics (Manus, iARM) [3] and Canadian Kinova (Jaco, Mico)[22]. These are lightweight, have integrated controllers and cost from USD 20,000-35,000 with a gripper. For example the Kinova JACO robotic arm [3] weighs 5.7kg (12.5lbs), comes with a wheelchair attachment kit. It can grasp, lift, and move objects up to 1.5kg. The Manus/iARM has similar specifications. Presently users control the robotic arm using a joystick, similar to conventional tele-operation[23]. Novel research user interfaces allow the user to specify an object to manipulate by either pointing towards it or clicking on it through a touch screen image; the robotic arm then moves to the target object and grasps it[24]. In published assistive robotics research a variety of other commercial robot arms are used, and several new prototype arms have been designed. However neither new robots, nor new research methods for motion control and HRI have reached significant deployment[25]. The few hundred deployed Jaco and Manus arms still use basic joystick position-based tele-operation, where a 2 or 3 DOF joystick is mapped to a subset of the Cartesian arm translation and wrist rotation controls[2]. To complete tasks in 6 DOF the user switches between modes for different joystick to arm DOF assignment, which can be tedious.

IV. A Task Taxonomy for Arm Manipulation

Robotics capabilities are built bottom-up, by designing sensing and control methods for individual motions. These motions can then be combined to solve tasks. The same motions can potentially be used to solve ADLs in quite different categories in the WHODAS/ICF taxonomy. Dextrous in-hand finger manipulation requires quite different contact configurations and manipulation taxonomies have been developed based on these contact configurations[26]. Robot arm manipulation is generally thought of uniformly as a 6 degree of freedom (DOF) Euclidean (end-effector) transform, requiring no taxonomy. Contrarily, ADL tasks naturally contain a variety of movements with different DOF, contact and precision requirements. This suggests that a taxonomy can guide development of control subroutines tailored to those requirements, and the composition of subroutines can solve a broad variety of tasks. Figure 3 introduces a high-level taxonomy of assistive robotics tasks, including arm manipulation. There are 3 general categories in assistive robotic applications: non-physical cognitive tasks, locomotion based mobility tasks, and arm-hand manipulation. We will focus on analyzing arm and hand motions. Currently in applied robotics, the robot hand is typically used for grasping, and the arm is responsible for pose alignment and contacts, possibly including force or impedance control. It will take some time before robotics will be able to utilize fine dexterous finger manipulation in actual applied ADLs, resulting in the arm performing both coarse and fine manipulations[17]. Coarse motion of the reach type is mostly a 3-DOF translation and has moderate accuracy requirements. Fine motion can be subdivided into contact and non-contact. Non-contact 6-DOF fine motion can be used to bring an object into alignment before putting it down or inserting it. Although most applied robotics is performed using position control, some studies take contacts into account,

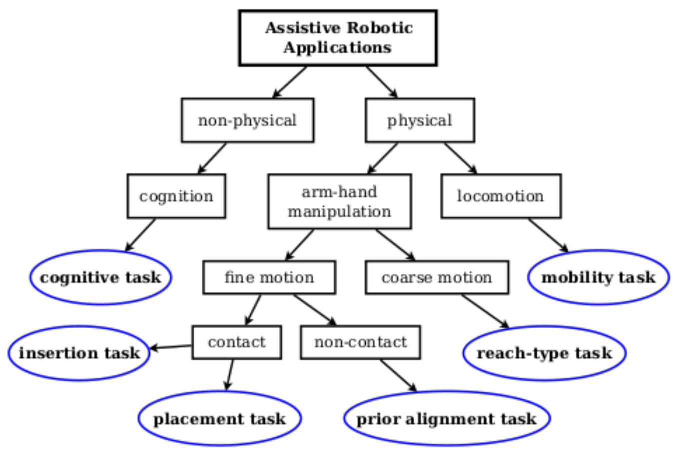

Fig. 3. Taxonomy of Assistive Robotics Tasks and Motions

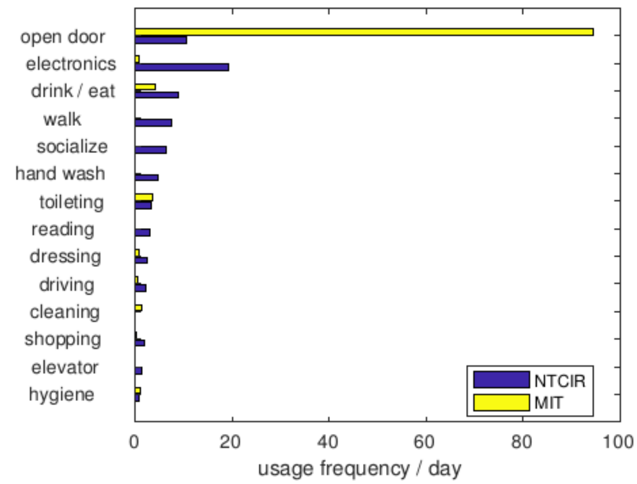

Fig. 4. Usage frequencies from sensors - MIT yellow bars, and video NCTIR blue bars.

either through impedance control, or sensing and modeling of the surface for hybrid position-force control[27]. Surface contacts allows human-like strategies to overcome sensing and actuation inaccuracies by utilizing practices such as touching a table and sliding fingers across it before picking up a small objects, such as a pen.

V. ADL Evaluation from Lifelogging Data

Lifelogging data is a valuable source of ADL, and human motion information. It involves long term recording of all the activities performed by a human, usually through a video camera, and occasionally other sensor data[10]. While lifelogging research has been published for more than two decades, hardware and method innovation has made the field grow greatly in the past five years. Small, wearable cameras, such as the Microsoft Lifecam, with long recording duration has made it far more practical compared to analog video cameras and recorders used in initial research. New methods for recognizing objects and actions has driven Computer Vision (CV) research interests to explore life-logging data, which has been found to be more realistic in-the-wild than typical CV benchmarks[28]. We studied over 30 lifelogging data sets, most of which targeted the performance of a particular algorithm (e.g. video object recognition in home environments), and therefore did not encompass the full day. As they typically did not have a statistically sound sampling over all objects and tasks to meet our analysis criteria . We found that long term recordings of several days or more were done at 1-2 frames per second (fps), making these useful to analyze ADL task frequency and duration, but not suitable for studying detailed timing of individual arm and hand motions. Another category of data sets had shorter 30fps regular video rate recordings of specific tasks, making the detailed timing of individual arm and hand motions possible. We were able to choose three sources of data for the analysis: two from long duration recordings to capture ADL task frequency and duration[10], [29], one from short term recording of tasks[30].

A. ADL Task timing analysis

To compute quantitative data on ADL task frequency and duration we analyzed both egocentric lifelogging videos (referred to as NTCIR), [29]and exocentric data from Internet-of-Things type sensing built into home objects (referred to as MIT) [29]. The use of complementary sensing turned out to be important to capture a broader set of tasks. Similar to other CV research, we were able to infer actions from automatically computed visual concepts[30]. We hand-labeled a small portion of the data to verify the accuracy of the automatic computations. This enabled us to label in-home data sequences spanning multiple days with what ADL users where performing at particular times and compute statistics. Figure illustrates the frequency of the most common ADL tasks.

We have grouped tasks to correspond to robot skills, rather than specific ADL/ICF codes. Commonly, events are not recorded in videos or from sensors as discussed below. By combining both results, we obtained an accurate quantitative measure of task importance.

Door openings is the most frequent task at 94/day, and includes both doors between rooms, cabinet doors, and drawers. Our rationale for including cabinet doors and drawers is that the robot would approach each situation in the same fashion as a standard door. We believe MIT data was more accurate when door opening data was obtained from built in door sensors; the low video frequency (2 fps) of the NTCIR data presented low accuracy with the automatic visual concepts extraction by missing quick openings, particularly of cabinet doors and drawers to retrieve objects. Following door opening, electronics refers to handheld devices, and was dominated by smart phone use. These devices were mostly not covered by the MIT sensors, but were detected by the NTCIR video. Drinking and eating were essential tasks in both studies, with a frequency of 8.8/day from NTCIR and 4.4/day from MIT. MIT based hand washing on the

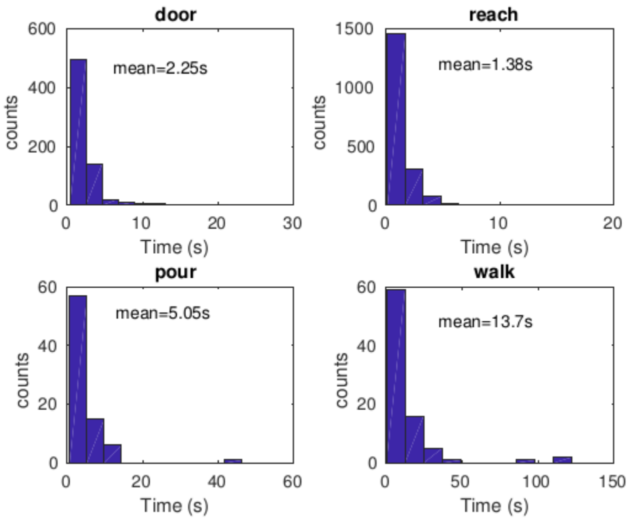

Fig. 5. Timings for four common human motions

number of faucet openings/closing (ie turning the sink on and off resulted in two tasks), which greatly overestimated hand washing. We removed this outlier and relied on NTCIR results of 4.7/day.

B. Arm and Hand Motion Analysis.

From other video datasets we were able to extract the number and timings of individual arm and hand motions needed to perform a particular ADL, and for a few tasks, similar timings for robot execution. The Georgia Tech Egocentric Activity Datasets (GTEA+) [1] contain full frame rate (30fps) video recordings of humans performing domestic tasks. We analyze the annotated GTEA+ dataset, which contained approximately 25GB of annotated kitchen activity videos. This allows for the extraction of individual human motion timings. Figure illustrates four common motions out of the 33 in GTEA+. Noteably, many human motions were far faster than typical assistive robot motions. For example reach motions take just a second for a human, while published HRI solutions take anywhere from ten seconds to several minutes[31]. This has implications for how many human motions and ADLs a robot system can practically substitute without tasks taking an excessive amount of time. In other motions, such as pouring liquids, the task itself constrains the human to proceed rather slowly. The door task covers both lightweight cabinet doors and drawers, along with heavier doors (e.g. refrigerator); with lighter doors, the human times approached that of unconstrained reach, despite the more challenging physical constraint of hinged or sliding motion. Unlike NTCIR, GTEA+ is not a representative sampling of all human activities. It is still notable that the number of reaches is three times the number of door openings. (1500 reaches versus 500 door and drawer openings over 11 hours of video).

[1] http://www.cbi.gatech.edu/fpv/

VI. Discussion

Of the measured ADL tasks, door openings, drinking/eating, hand wash and toileting would arguably be the most essential to support for assistive robot arm and hand systems. These tasks are relatively feasible to accomplish given the payload capacity of current arms.

Activities such as using electronics (primarily smartphones), socializing, and reading could be physically aided by robot arms, but since these activities are not inherently physical, alternative solutions are possible and can be simpler and more reliable (e.g. hands-free phone use and other computational automation).

Toileting is a priority task that involves transferring those with disabilities from a wheelchair to the toilet. Assistive arms do not support this, but there are specialized transfer devices - also useful for transfer from beds - that are generally used in health care, and could potentially be employed in homes.

Overall, there is great potential for supporting ADLs for those with disabilities and the elderly. Over the past few decades there has been an increasing demand for health care services due to the rising elderly and disability populations [32]. Assistive robots can bridge this gap by alleviating the labour burden for health care specialists and caregivers. Moreover, an assistive robot could help one perform ADL they are otherwise incapable of managing on their own, returning individual independence. Canada has a multi-ethnic population and characteristics similar to many other industrialized nations. Statistics Canada found that from 2001 - 2006 there was a 20.5% increase in those identifying as having a disability, rising to 4.4 million people [33]. The proportion of seniors (age 65+) in the population has also steadily increased, with seniors comprising a projected 23.1% of the population by 2031 [34]. In 2014, seniors constituted only 14 of the population, but consumed 46% of provincial public health care dollars [35]. Functional capacity is an indicator of ones ability to carry out ADL, and as one ages, losses in functional capacity become more common and severe, leading to required assistance with ADL. Statistics Canada further states that over 2.4 million people living with disabilities regularly receive assistance with at least one ADL on a daily basis, with immediate family members most commonly identified as the primary caregiver. It has been shown that the number of ADL requiring assistance is correlated with the severity of the disability [33]. Using a robotic arm attached to a wheelchair would help users to gain the freedom to complete more of their daily tasks independently.

VII. Conclusions

In this paper we presented assistive robotics for Activities of Daily Living both from a health care perspective and robotics perspective. We analyzed human ADL task frequency from public life-logging datasets and computed motion timings from public Computer Vision data. Overall, reach motions (to grasp objects) and door openings (including cabinets and drawers) were the most frequent motions. Drinking, eating and hand washing are other high priority tasks that can be addressed by current assistive robot arms. Toileting and dressing, while ranking just below, are generally thought to be more challenging for robotics, since they require the transfer of substantial body weight. Detailed data on frequency and duration information for all analyzed tasks and motions, as well as the analysis methods are available on the companion website `http://webdocs.cs.ualberta.ca/~vis/ADL`

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